Optimizing Product Design through a Particle Swarm Induced Logistic Regression Model

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Abstract: This paper defines how a meta heuristic search engine called P.S.O can be used to maximize the objective function of a logistic regression model, describing the relationship between the response variable (product designs' score) and a set of explanatory variables (product design factors). At the first phase the processed data, classified and categorized, by Kansie Engineering is used as input to the logistic regression model. The PSO optimization algorithm, maximizes the likelihood function, thus the parameters of the model, being the coefficients of the independent factors are estimated. After post hoc tests, the validated model, defines the relation between consumer semantic and physical product selection factors and the response variable which is a dichotomous dependent ordered variable representing product design scores.

Keywords: Kansie Engineering- Logistic Regression- Particle Swarm Optimization (P.S.O)- Product Design.

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1 INTRODUCTION

Interest in creating quantifying links between product properties and user impressions has existed for a long time. Research on this question has been done before in different areas, e.g. QFD [1] and conjoint analysis [2] in TQM. However, a deeper look reveals that the user's perception is a very complex formation alluding to many different scientific fields, namely mechanical engineering, Quality/ Mathematics, and Ergonomics [3] Hence, the role of kansei engineering in this context is to tunnel through the borders between the different scientific fields, identifying suitable tools and reassembling them in to new methods. In fact, kansei engineering does not develop new theories or tools in the different areas at all. Rather, it is an all-embracing methodology containing rules for how different tools can interact with each other in order to quantify the impact a certain product trait has on the user's perception. Nowadays, products are generally conceived as complying with high standards of quality, and the consumer's purchasing criteria change more to preference-related characteristics as he is accustomed to enjoy high quality products. That is when consumers purchase a product; their preference is influenced by design quality as well as by functionality. Thus if the design of a product meets the specific needs and feelings of consumers, it will be more likely to be purchased. In many cases, experts are more aware of the user's demands than the users themselves. On the other hand, users can easily assess whether a product is suitable in a certain respect or not and his research group have developed a number of different statistical procedures using different mathematical implements to capture the user's impression such as [4].

- Linear regression [5]
- General Linear Model (GLM) [6]
- GT1 [7]
- Neural Networks [8]
- Genetic Algorithm [9]
- Rough set Analysis [10]

The aim of this paper is to introduce a new algorithm inducing kansei engineering expert system in product development, called: Particle Swarm Optimization. (P.S.O) In the following article, essential definitions of kansei engineering, and the P.S.O algorithm, is given, then a conceptual model of a typical logistic regression induced by the P.S.O optimizer is introduced, followed by a discussion and conclusion.

2 KANSEI ENGINEERING EXPERT SYSTEMS

The Japanese word, kansei; has a meaning of 'feeling', 'impression' and/or 'emotion'. Kansei engineering is a method for translating a consumer's image or feeling in to real design components and kansie engineering expert systems (KES) are the computer systems that support consulting sales or product design [11], [12]. Kansei engineering, as an ergonomic consumer-oriented technology, enables a consumer's image or feeling to be incorporated in the design process of a new product. Kansei engineering expert systems are computer systems that employ kansie engineering for analyzing human kansei. The architecture of the system is shown if figure 1. The system is composed of three basic modules. Adjective processing module, inference engine and graphic module. The system has two types of reasoning processes: kansei reasoning and design reasoning. The former process, also called forward infers the design [11]. Specifications from human kansei, whereas, the latter process, also called Backward, infers the human kansei represented by adjective words from the design elements.

The information of human kansei is stored in the image database which consists of the results of the statistical analysis according to the customer characteristics such as age and gender. The procedure of the forward reasoning is as follows: A user enters in to the system one or more adjective words representing his kansei, or simply the user requirement. Here, all adjectives used to describe a product can be considered as kansei words. The adjective processing module searches the adjective database to translate user-inputted adjective in the basic adjectives that were collected in advance from magazines and shops and were stored in the database. The reasoning module then analyzes the relationship between translated words and human image from the image database, and a design arrangement. At the same time, it refers to the knowledge base to check if conflicts exist between design items. The graphic module processes the inferred design using the graphic database. Kansei engineering systems are designed for the following functions.

1. Communication between designer and customer.
2. Customer support for the selection of products.
3. Designer support for the evaluation of kansei design.

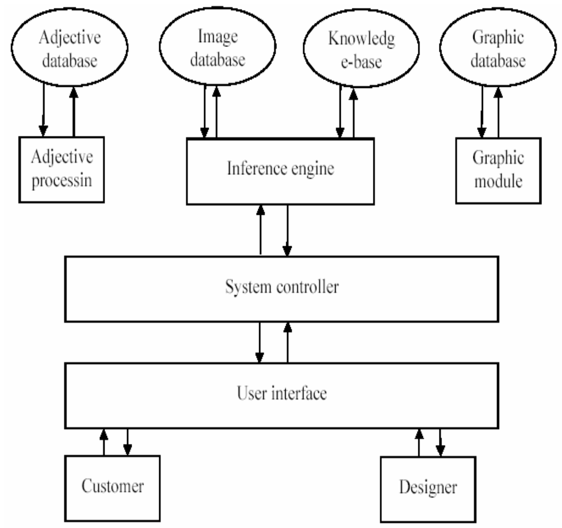

Fig. 1 The architecture of kansei engineering systems (KES).

In the classic statistical methods, two major difficulties existed: First, It is very difficult to extract a set of effective variables from a large number of designs. Second, The classic models are unable to represent the dependence between design attributes, since human perceptions to the combined effects of various design items are very complex and ambiguous. The use of different tools depends on the context. Emotions and feelings do not follow mathematical laws. Sometimes it is possible to use linear methods, which are easiest to handle, sometimes more complex models have to be applied. The outcome of all tools describes only in which way the kansei words are correlated to the product properties. Statistical analyses play an important role in the KES. Hayashi's quantification theory-type I, has been used as the most useful statistical tool in the KES [7].

The linear regression model of quantification theory type I provides good relational data to derive a relationship between human perception and product design factors. However the model has several shortcomings. It assumes. that all predictors are linearly related to each other yet, in many cases, the combination of different design factors yields a distinct perception of the design. When explanatory variables correspond to each design factor and a dependent variable corresponds to quantitative measures of human perception, there is usually an interaction or dependency between design factors. It is rarely possible to consider these interactions, with the classic model. In other words, the model does not suffice to describe the whole design effectiveness composed of many design factors, although it fairly estimates the amount of influence of a single attribute. Another difficulty is that there are too many factors to design a product. The classic model has a statistical constraint about the number of variables. If we wish to analyze concurrently the effect of numerous design aspects, we must increase the number of evaluation samples related to the product design. In reality, however, the number of design alternatives for evaluation is constrained by the limited time and budget. A means to solving this problem is to choose carefully the most influential design factors. However, this is also a difficult concept to apply when the design item to be evaluated becomes too expensive or large in size. To solve these problems a method is proposed in this study to acquire the knowledge for the KES in the cases that have many design attributes. In the presented method, P.S.O algorithm is used.

3 PARTICLE SWARM OPTIMIZATION (PSO)

The metaheuristic particle swarm optimization (PSO) was proposed by Kennedy and Eberhart [13]. Kennedy and Eberhart were inspired by the behaviors of bird flocking. The basic idea of the PSO met heuristic could be illustrated by using the example with a group of birds that search for a food within some area. The birds do not have any knowledge about the food location. Let us assume that the birds know in each iteration how distant the food is. Go after the bird that is closest to the food is the best strategy for the group.

Kennedy and Eberhart treated each single solution of the optimization problem as a "bird" that flies through the search space. They call each single solution a 'particle'. Each particle is characterized by the fitness value, current position in the space and the current velocity [14]. When flying through the solution space all particles try to follow the current optimal particles. Particle's velocity directs particle's flight. Particle's fitness is calculated by the fitness function that should be optimized.

In the first step, the population of randomly generated solutions is created. In every other step the search for the optimal solution is performed by updating (improving) the generated solutions. Each particle memorizes the best fitness value it has achieved so far. This value is called Pbest. Each particle also memorizes the best fitness value obtained so for by any other particle. This value is called gbest. The velocity and the position are changed in each step. Each particle adjusts its flying by taking in to account its own experience, as well as the experience of other particles. In this way, each particle is loaded towards pbest and gbest positions. The position $X_i = (X_{i1}, X_{i2}, ..., X_{iD})$ and the velocity $V_i = (V_{i1}, V_{i2}, ..., V_{iD})$ of ith particle are vectors. The position X^i_{K+1} of the ith particle in the (K+1) st iteration is calculated in the following way:

$$X^i_{K+1} = X^i_K + V^i_{K+1}\Delta t \tag{1}$$

where X^i_{K+1} is the velocity of the i th particle In the (K+1) st iteration and Δt is the unit time interval. The velocity X^i_{K+1} equals:

$$V^i_{K+1} = \omega V^i_K + C_1 r_1 \frac{(PB^i - X^i_K)}{\Delta t} + C_2 r_2 \frac{(P^g - X^i_K)}{\Delta t} \tag{2}$$

where ω is the inertia weight, r_1 and r_2 are the random numbers (mutually independent) in the range $[0,1]$, C_1, C_2 are the positive constants, PBi is the best position of the i th particle achiever so far and Pg is the best position of the i th particle achieved so far. And Pg is the best position of any particle achieved so far. The particle's news velocity is based on its previous velocity and the distances of its current position from its best position and the group's best position. After updating velocity the particle flies toward a new position (defined by relation (2)). Parameter as that represents particle's inert ion was proposed by shi and Eberhart [15]. Parameter ω that represents particle's insertion was proposed by Shi and Eberhart. Parameters C1 and C2 represent the particle's confidence in its own experience, as well as the experience of other particles. Venter used the following formulae to calculate particle's velocity:

$$V_{K+1}^{i} = \omega V_K^i + C_1 r_1 \frac{(PB^i - X_K^i)}{\Delta t} + C_2 r_2 \frac{(P_K^g - X_K^i)}{\Delta t} \qquad (3)$$

In other words, when calculating the particle's velocity, Venter replaced the best position of any particle achieved so far Pg, by the best positing of any particle achieved in the Kth iteration P_K^g. The PSO represents search process that contains stochastic components (random numbers, r_1 and r_2). Small number of parameters that should be initialized also characterizes the PSO. In this way, it is relatively easy to perform big number of numerical experiments. The number of particles is usually between 20 and 40. The parameters C_1 and C_2 are most frequently equal to 2. When performing the PSO, the analyst arbitrarily determines the number of iterations. Here by a pseudo code of this algorithm is presented:

```
# Initialize the particle positions and their velocities
X = lower_limit + (upper_limit - lower_limit) * rand
(n_particles, n_dimensions)
Assert X.shape == (n_particles, n_dimensions)
V = zeros (X.shape)

# Initialize the global and local fitness to the worst possible
fitness_gbest = INF
fitness_lbest = fitness_gbest * ones (n_particles)

# Loop until convergence, in this example a finite number
of iterations chosen
For k in range (0, n_iterations):
   # evaluate the fitness of each particle
   fitness_X = evaluate_fitness(X)

#  Update the local bests and their fitness for I in range (0,
n_particles):
If fitness_X [I] < fitness_lbest [I]:
fitness_lbest [I] = fitness_X [I]
For J in range (0, n_dimensions):
X_lbest [I] [J] = X [I] [J]

# Update the global best and its fitness
min_fitness_index = argmin (fitness_X)
min_fitness = fitness_X[min_fitness_index]
If min_fitness < fitness_gbest:
fitness_gbest = min_fitness
X_gbest = X[min_fitness_index,:]

# Update the particle velocity and position for I in range(0,
n_particles): for J in range(0, n_dimensions):
R1 = uniform_random_number ()
R2 = uniform_random_number ()
V [I] [J] = (w*V [I] [J]
+ C1*R1*(X_lbest [I] [J] - X [I] [J])
+ C2*R2*(X_gbest [J] - X [I] [J]))
X [I] [J] = X [I] [J] + V [I] [J]
```

4 MODEL SPECIFICATION

In constructing a kansei engineering system, the knowledge acquisition for the image data base of kansei reasoning and design reasoning is based on the experiments using actual design samples, e.g., cars, clothing etc. In the experiment, subjects are asked to test various design samples and to evaluate them with the questionnaires based on the semantic- differential technique [16]. In the present model, the actual design factors are a set of dependent variables and the semantic- differential data used as independent variables as depicted in figure 2.

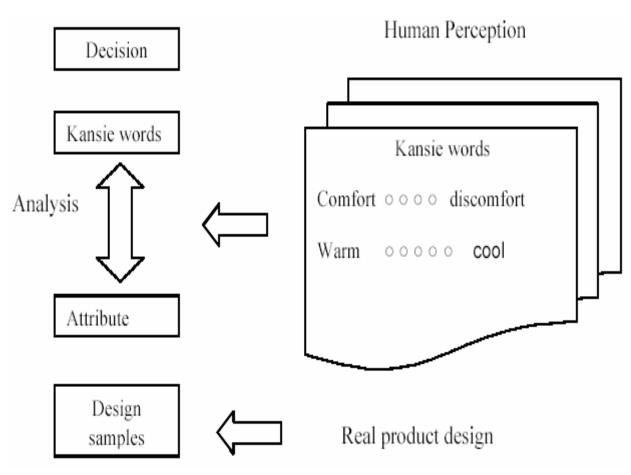

Fig. 2 the questionnaire used in the Kansie evaluation experiments and its analysis.

The subjects chosen are supposed to rate words of objects on bipolar scales. These scales are defined with a number of contrasting adjectives at each end on which the participants check the position which best represent the direction and intensity according to their point of view. An example of the scale type used is shown in figure 3.

Interior dimensions of a vehicle: comfort ■□□□□ discomfort

Fig. 3 Example of a 5-point rating scale

Finally each factor contained in each category is graded and an input file containing graded factors of sample consumers is recorded. Each consumer’s point of view is now accounted as a case record, fed in to the model. Now the dependent variable y should be introduced and categorized y is a dichotomous variable. Multinomial Logistic Regression is useful for situations in which subjects are to be classified based on values of a set of predictor variables. This type of regression is similar to logistic regression, but it is more general because the dependent variable is not restricted to two categories.

5 MULTINOMIAL LOGISTIC REGRESSION

Regression methods have become an integral component of any data analysis concerned with describing the relationship between a response variable and one or more explanatory variables [17]. It is often the case that the outcome variable is discrete, taking on two or more possible values. Over the last decade the logistic regression model has become, in many fields, the standard method of analysis in this situation. The linear logistic model assumes a dichotomous dependent variable Y with probability π, where for the ith case,

$$\pi i = \frac{\exp(\eta i)}{1+\exp(\eta i)} \tag{4}$$

Or

$$\ln\left(\frac{\pi i}{1-\pi i}\right) = \eta i = X'\beta \tag{5}$$

Hence, the likelihood function l for n observations, $y_1, \ldots y_n$, with probabilities, $\pi_1, \ldots \pi_n$, and $\omega_1, \ldots \omega_n$, case weights, can be written as

$$L = \prod_{i=1}^{n} \pi_i^{y_i \omega_i} (1-\pi_i)^{\omega_i (1-y_i)} \tag{6}$$

It follows that the logarithm of l is

$$L = \ln(l) = \sum_{i=1}^{n} w_i y_i \ln(\pi_i) + w_i (1-y_i) \ln(1-\pi_i) \tag{7}$$

And the Derivative of L with respect to β_i is

$$L_{XJ} = \frac{\partial L}{\partial_{\mathrm{B}_J}} = \sum_{i=1}^{n} w_i (y_i - \pi_i) X_{IJ} \tag{8}$$

6 DISCUSSION

The likelihood function obtained from the multinomial logistic regression which relates the dependent variable (y) to independent product attributes (x) can be used as a fitness evaluator in the p.s.o algorithm Particle's fitness is calculated by the fitness function that should be optimized. In the first step, the population of randomly generated solutions is created. In every other step the search for the optimal solution is performed by updating (improving) the generated solutions. Improvement is reached at by the function derived from logistic regression model. in the final iteration of the algorithm, when near convergence of the particles has been reached, the best particle's position contains attributes contributing to the highest design score in consumer's point of view, thus the optimal design parameters are acquired.

In Table 1 kansie data obtained from a case study implemented upon 52 elderly consumers comparing 4 optional designs for locomotion facilities are depicted. Factors such as self confidence, locomotion, Ergonomy, comfort, effectiveness, balance, control, agility, independence, simplicity in use, power, reliability, interactive design, integrate the best score to optional design no. 1, from aspects such as having a pleasant experience, pleasurability, coordination, attractiveness, amicability, enthusiasm, and having an inclusive design. Optional design no. 3 rates highest. When acquiring these data not only consumer's answers were recorded but their facial and tactile reactions were also noticed. Among the independent variables contributing to the optimal design,

1- having broader touching surface at the bases

2- repetitive vertical lines

3- compactibility

can be extracted as critical factors. The final pilot design was decided to have the combined properties of both optional design 1 and 3.

Table 1: kansie data gathered from consumers related to the pilot survey

kansei Words	plan no 1	plan no 2	plan no 3	plan no 4
Balance	0.5	0.096	0.308	0.096
Effectiveness	0.529	0.098	0.255	0.118
Comfort	0.5	0.096	0.308	0.096
Ergonomy	0.538	0.077	0.25	0.135
locomotion	0.431	0.137	0.314	0.118
Self Confidence	0.42	0.1	0.34	0.14
pleasant Experience	0.346	0.077	0.5	0.077
Enthusiasm	0.327	0.077	0.519	0.077
Amicability	0.346	0.096	0.481	0.077
Pleasure	0.308	0.096	0.519	0.077
Agility	0.46	0.08	0.34	0.12
Control	0.519	0.115	0.251	0.115
Attraction	0.373	0.078	0.451	0.098
Coordination	0.373	0.078	0.451	0.098

7 CONCLUSION

Predicting optimal product design factors, by the classic statistical methods, have two major difficulties; firstly, it is very difficult to extract a set of effective variables from a large number of designs, secondly, the classic models are unable to represent the dependence between design attributes. Since human perceptions to the combined effects of various design items are very complex and ambiguous; as such being the case, in this study, a mixed classic and heuristic method was developed in which initial product attributes were inferred through a kansie expert system and processed through a two phased optimizing search method. At the first phase the processed data, classified and categorized by Kansie engineering was used as input to a logistic regression model; then the response variable defined in this phase was used as a fitness evaluator for the P.S.O algorithm. According to this fitness score a better solution is obtained every time the algorithm runs an itreation and when stopping criterion is reached the solution has the optimal factors or covariates stored in its position vector.

8 NOMENCLATURE

n= the number of observed cases

p= the number of parameters

y = n×1 vector with element y_i, the observed value of the ith case of the dichotomous dependent variable

β = p×1 vector with element βj, the coefficient for the jth parameter

ω = n×1 vector with element wi, the weight for the ith case

l= Likelihood function

L = Log-likelihood function

I = Information matrix

X_i = position vector for the particle

V_i = Velocity vector for the particle

Δt =time interval

pb^i = best position of the ith particle

p^g = best position of any particle

C_1 = random number

C_2 = random number

ω = inertia coefficient

Σ = summation

$\prod$ = product

9 ABREVIATIONS

P.S.O= particle swarm optimization

QFD= quality function deployment

TQM= total quality management

KES= kensie engineering system

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